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A Decision-Making System Based on Machine Learning for Commercial Credit Limit

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Ticari Kredi Limiti için Makine Öğrenimine Dayalı Bir Karar Destek Sistemi

Abstract

This research presents a novel machine learning model that adjusts commercial credit limits based on financial audit data, offering an alternative to traditional models that categorise customers as either 'good' or 'bad.' It identifies key variables for banks' credit rating processes, improving existing methods. The model ensures objectivity by focusing on financial data from independent audits and excluding past behaviour. The study proposes a classification system for credit limits as "increasing" or "decreasing", aiming to attract new customers. The random forest achieved the highest success rate of 69.40% among the algorithms tested.

Keywords : Classification, Machine Learning, Credit Rating, Feature Selection.

JEL Classification Codes : C52, G24, G32.

Öz

Bu araştırma, kredi limiti ayarlamalarını doğru bir şekilde sınıflandıran ve bankaların ticari kredi derecelendirme süreçleri için kritik değişkenleri belirleyen bir makine öğrenimi modeli sunmaktadır. Bankalar, kötü kredileri en aza indirirken geliri maksimize etmeyi hedeflemekte, bu da hassas müşteri sınıflandırmasını gerektirmektedir. Bağımsız denetim raporlarındaki finansal değişkenlere odaklanan bu çalışma, nesnelliği sağlamak amacıyla geçmiş müşteri davranışlarını dikkate almamaktadır. Ayrıca, "artan" ve "azalan" limitleri ayıran bir sınıflandırma sistemi önererek kredi derecelendirme literatüründeki eksiklikleri gidermeyi amaçlamaktadır. Çalışma, çeşitli algoritmaları değerlendirerek rastgele orman algoritmasının %69,40 ile en yüksek başarıyı elde ettiğini göstermektedir.

Anahtar Sözcükler : Sınıflandırma, Makine Öğrenmesi, Kredi Notu, Özellik Seçimi.

1. Introduction

Financial institutions are increasingly adopting credit rating models that utilise data mining algorithms to enhance decision-making and mitigate losses resulting from poor credit choices. Credit ratings are used to predict the risk associated with a customer (Tripathi et al., 2018). Lenders can assess repayment potential through credit ratings, which gauge the risk associated with a company's ability to repay a loan. Credit ratings are crucial for financial risk management and have become a central focus for the banking sector. Accurate evaluation of loan applications is crucial, as even minor errors (1%) in credit ratings can result in substantial losses for banks (Pławiak et al., 2019).

Today, credit rating is a primary concern for banks, as it addresses risk-related uncertainties. Effective risk management enables banks to establish a robust decision-making framework and reduce losses. Credit risk, which accounts for 60% of total bank risks, is acknowledged as a complex challenge in risk assessment (Soui et al., 2019). While this 60% rate applies to deposit banks, it is higher for investment banks and crowdfunding instruments that provide financing through deposit collection.

Credit risk refers to the possibility that a company may fail to meet its obligations, become bankrupt, and default on its debts. Credit risk is significant for banks (Georgios, 2019). The success of banks relies on their ability to accurately assess credit risk. Their goal is to maximise revenue while minimising bad loans, as poor loans can undermine profits from successful ones. Thus, banks carefully evaluate the financial status and creditworthiness of each customer. Credit risk assessment models in the literature predominantly involve regression techniques and machine learning methods, widely used for financial forecasting and multi-criteria decision-making (Abellán & Castellano, 2017; Bussmann et al., 2020; Giudici et al., 2019; Khandani et al., 2010; Khashman, 2011; Lessmann et al., 2015). Many studies in the literature discuss credit rating models that utilise machine learning classifiers. Moreover, creating a predictive model for credit rating is a potential research area (Trivedi, 2020).

Credit rating, in addition to traditional statistical methods, is an important research area in which data mining approaches, particularly machine learning-based studies, are continually evolving. In studies involving machine learning, it appears possible to improve decisions without relying on strict statistical rules (Altman, 1968; Chen et al., 2016; Ziemba et al., 2021).

Machine learning is frequently used in the financial field to develop expert-based credit risk models (Munkhdalai et al., 2019). Credit rating, one of the most significant risks in the banking sector, has attracted considerable research interest. Scholars are increasingly focused on developing new models that outperform existing ones. The growing significance and superior accuracy metrics have spurred increasing research interest in employing machine learning techniques for credit risk assessment (Bhatore et al., 2020). These methodologies aim to mitigate the shortcomings of individual classifiers while enhancing their efficacy (Abedini et al., 2016).

In recent years, credit ratings have become a growing concern for financial institutions and are now a popular research topic (Zhang et al., 2018). Upon examining the existing literature on credit rating, it becomes evident that classifications are typically limited to "acceptance" or "rejection". This study, in contrast, aims to introduce a machine learning model capable of categorising a customer's current credit limit as either "increasing" or "decreasing". While previous models have focused solely on positive or negative outcomes, this study offers valuable decision support for bank officials in adjusting existing credit limits. Banks can mitigate the risk of future credit defaults by proactively managing credit limits. Furthermore, rather than simply accepting or rejecting a customer's request for a new credit limit, banks could incrementally raise the existing limit, enhancing customer satisfaction and bank profitability. This model distinguishes itself by allowing for a dynamic response. When new data is input into the trained machine learning algorithm, the output may indicate an increase or decrease in the company's credit limit. To our knowledge, the classification of commercial credit line direction, whether increasing or decreasing, using machine learning techniques has not been explored previously in the literature.

In the literature, machine learning studies on credit rating primarily focus on distinguishing creditworthy from non-creditworthy customers using historical data. This approach typically applies classification techniques to identify characteristics associated with credit failure. However, these methods may struggle to accurately predict credit ratings for business customers due to data sparsity and incompleteness (Kumar-Roy et al., 2023).

The reliance on historical customer behaviour data raises concerns about the practical applicability of credit rating research for banks. Institutions require decision-making capabilities based on data that reflects future potential, as relying solely on past metrics can lead to missed opportunities and increased risk. To address this challenge, this study utilises independent audit reports made available as open data, thus overcoming the limitations identified in existing literature. Unlike prior studies, which often focus on the past behaviour of commercial customers, this research includes potential new customers, recognising that understanding future behaviour is crucial for sustainable growth. By specifically targeting commercial loans, this study addresses the unique requirements of commercial credit evaluation and provides valuable insights into the field. Additionally, the integration of feature selection methods with machine learning algorithms in credit assessment remains a limited area of research. This study enhances the existing literature by employing these techniques to identify key variables critical to the commercial credit rating process, thereby improving the accuracy and reliability of the model.

In summary, this research presents a novel machine learning model that can classify credit limits and identify relevant variables, thereby enabling banks to make more informed and strategic credit decisions. By focusing on potential new customers and leveraging machine learning techniques, this study provides a crucial foundation for innovations in commercial credit evaluation. It enhances banks' ability to predict credit limits accurately.

The remainder of the paper is structured as follows: First, a comprehensive literature review delves into existing studies. The research methodology employed is then elucidated. Section 4 outlines the proposed model. The paper concludes with final remarks and avenues for future research.

2. Literature

The literature studies on the variables affecting credit ratings for loans extended by banks, as well as the classification estimation algorithms used in the research, are presented below in the subheadings.

2.1. Credit Rating and Machine Learning

Upon reviewing the studies on credit rating in the literature, it becomes apparent that most of these focus on employing machine learning algorithms to assess loans for individual customers. For example, Turkson et al. (2016) applied 15 different machine learning algorithms and compared them using credit card data from individual bank customers in Taiwan. All but two algorithms (Nearest Centroid and Gaussian Naive Bayes) have an accuracy rate of 76% to 80%. According to the study results, credit card default due diligence was completed using machine learning algorithms. Amanze et al. (2019) developed a machine learning-driven digital nervous system model to assess individual credit lines at a Nigerian bank. Real credit card data from the UCL open database was used to test the model. In the study, which involved classifying transactions as either paying or defrauding the credit card, the proposed model and CART, ANN, and NB algorithms were compared, yielding the highest success rate of 83% accuracy with the proposed model. Similarly, Massahi Khoraskani et al. (2017) applied ANN, LR, and CART algorithms, considering 24 criteria in 1,000 loan applications from individual bank customers in Germany. Model performance criteria, precision, sensitivity, and accuracy rate were compared with performance measures. According to the study results, which classified customers as low-risk and high-risk, the ANN algorithm demonstrated superior success in credit risk assessment compared to other algorithms. Additionally, Zurada and Zurada (2002) analysed a bank's personal loan data using ANN, LR, CART, and an ensemble model that combined these methods to predict loan repayment. The study assessed the effectiveness of each technique in comparing default risk. Findings showed that the ensemble model outperformed the others. Furthermore, Pławiak et al. (2020) proposed an integrated method, combining different estimation methods, including ANN, SVM, KNN, and fuzzy systems, for retail loan customers. Classification was made based on accepted and rejected applications. The method proposed in this study achieved a success rate of 94.60% in credit rating estimation.

While some researchers examined individual loans using different techniques, they also evaluated the variables associated with them. Koçoğlu and Ersöz (2021) compared the

LR algorithm, a traditional crediting method, with the SVM machine learning technique. Their findings showed that SVM outperformed LR in accuracy and prediction rate. In the SVM model, "Credit policy" was the most critical variable, whereas "Interest rate" was the key variable in the LR model. Both models ranked "Income" as the third most significant variable. Experts preferred "Credit policy" in the SVM model, underscoring its greater realism and the overall superiority of the SVM approach. In another study by Ersöz et al. (2016), customers seeking loans at a bank branch underwent analysis using data mining techniques. The research encompassed data such as loan amounts used by individual and SME customers associated with the bank branch, instalment numbers, occurrences of delays in loan repayments, ongoing payments at other banks, and the number of banks from which they borrowed. The classification task was examined using the CART algorithm. Ultimately, the study culminated in the determination of risk categories for the customers. Similarly, Boz et al. (2018) used LR, CART, SVM, and RF algorithms to classify customers as good or bad based on demographic and payment information, including loan amount, age, loan term, education level, and housing status. The study found that SVM and RF algorithms performed best. The importance of variables, ranked from highest to lowest, was as follows: consumer reporting score, age, length of employment, net income, education level, homeownership, car ownership, and marital status. Gahlaut et al. (2017) analysed a bank's past relationships with individual customers using six machine learning algorithms to classify customers as good or bad. The dataset included 18 variables: age, occupation, marital status, and other demographic characteristics. The algorithms employed were CART, RF, SVM, LR, ANN, and AdaBoost. Results showed that the RF algorithm achieved the highest accuracy. The other algorithms were also deemed unsuitable as binary classifiers for datasets with many categorical variables. While all variables positively influenced the target variable, three loan repayment terms, loan amount, and borrower age were found to have a negative impact on creditworthiness.

Commercial credit rating and machine learning studies, which are rarely seen in the literature, are summarised as follows;

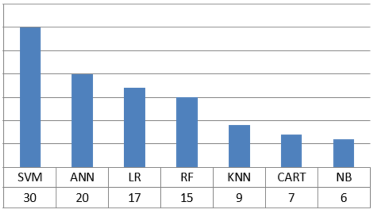
Zekic-Susac et al. (2004) compared credit rating performances for commercial loans in Croatia using ANN, LR, and CART algorithms. Key variables included loan interest rate, loan amount, grace period, and whether the company is new, with the dependent variable classified as "good" or "bad". Data were collected randomly, yielding a sample of 166 credits. The ANN model demonstrated greater predictive power than the LR and CART algorithms, utilising a dataset of 31 variables. Significant variables included interest rate, grace period, principal repayment mode, primary business activity, competitive awareness, company vision, and applicant profession. Similarly, Kavcıoğlu (2019) compared ANN and classical methods to reduce banks' credit risk in commercial credit rating in Türkiye. The dataset comprised 128 variables from the balance sheets, income statements, and cash flow statements of credit-seeking companies. Although the ANN algorithm performed well, the LR analysis provided more consistent results. Key bankruptcy predictors within 12 months included the firm's net debt, the proportion of cash, and similar items as a percentage of total assets. In another study, Hu and Su (2022) analysed the financial data of 150 companies to assess commercial credit ratings using the K-means algorithm, without classifying loan acceptance or rejection. The study aimed to compare algorithm performance by integrating cluster analysis with an ANN model, evaluating two traditional credit risk models against three neural network models. The results showed that the ANN model had the highest predictive capability among all the tested models. Giannouli and Kountzakis (2019) ranked commercial credit risk by combining financial data with credit behaviour data from three major banks in Greece. Key variables included loan utilisation patterns, comparisons of recent defaults with historical defaults, and factors like bad checks and default history. The performance of a financial-only model was compared to one that included credit behaviour for classifying companies as “good” or “bad”, using logistic regression (LR) for analysis. Results showed that the combined model significantly outperformed the financial-only model in classification success.

Table: 1
Credit Rating Literature Summary

No	Author (s)	Techniques Used						
		SVM	ANN	LR	RF	KNN	CART	NB
1	Bellotti et al. (2011)	x						
2	Loterman et al. (2012)	x	x					
3	Brown and Mues (2012)	x	x	x				
4	J. Wang et al. (2012)			x				
5	Akkoç (2012)		x	x				
6	Kao et al. (2012)	x	x				x	
7	Kim and Ahn (2012)	x	x					
8	García et al. (2012)	x						
9	Nikolic et al. (2013)			x				
10	Blanco et al. (2013)		x	x				
11	Harris (2013)	x						
12	Niklis et al. (2014)	x		x				
13	C. C. Chen and Li (2014)	x						
14	Shen and Jia (2014)	x	x	x				x
15	Bravo et al. (2015)		x	x				
16	Abdelmoula (2015)					x		
17	Koutanaei et al. (2015)	x	x					
18	Harris (2015)	x	x	x				
19	Danenas and Garsva (2015)	x	x					
20	Turkson et al. (2016)	x		x	x	x	x	
21	Ala’Raj and Abbod (2016)	x	x	x				
22	Ozturk et al. (2016)	x			x	x	x	x
23	Gahlaut et al. (2017)	x	x	x	x			
24	Luo et al. (2017)	x	x	x				
25	Zhang et al. (2018)	x		x	x	x		
26	Zhu et al. (2018)			x	x			
27	Feng et al. (2019)	x				x		x
28	Y. Wu et al. (2019)	x			x			
29	Beutel et al. (2019)	x			x	x	x	
30	Pławiak et al. (2019)	x				x		
31	Trivedi (2020)	x			x			x
32	Li et al. (2020)	x	x		x		x	
33	Golbayani et al. (2020)	x	x		x		x	
34	Fonseca et al. (2020)		x					
35	M. Wang and Ku (2021)	x	x		x			
36	C. F. Wu et al. (2021)	x						x
37	Zhao (2021)	x					x	
38	Colozza et al. (2022)	x						
39	Yu et al. (2022)	x	x		x		x	
40	He et al. (2022)			x	x			
41	Runchi et al. (2022)	x		x	x	x		
42	H. Wang et al. (2022)	x	x		x	x		
43	Kriebel and Stitz (2022)				x			x
44	T. Wang et al. (2022)	x			x	x		
	Number of Choices	**34**	**20**	**17**	**15**	**10**	**8**	**6**

The format for presenting the literature review results is shown in Table 1. This table summarises the algorithms employed in the 44 studies reviewed for the research. According to the results of the literature review presented in Table 1 above, seven methods are frequently utilised in the literature. The distribution of techniques used in scientific studies related to machine learning-based credit scoring is presented in Fig. 1. In this study, the SVM, ANN, LR, RF, CART, and NB algorithm methods were employed to compare prediction successes. After the literature study, machine learning algorithms and independent variables to be used in this study were selected.

Figure: 1
Credit Rating Literature



2.2. Credit Rating and Feature Selection

Today, numerous variables are associated with customers, and the large data sizes of these variables necessitate that banks develop credit rating methods by exploring various solutions to inform credit decisions. In high-dimensional datasets, it may be necessary to reduce the number of variables in the model by investigating the possibility that not all measured variables are essential to understanding the model. Feature selection is a method that can reduce both data and computational complexity. Thanks to this technique, the dataset can become more efficient, and the division of data into subsets can be helpful in model analysis (Azhagusundari & Thanamani, 2013). According to the authors' research, few studies in the literature utilise the feature selection technique across machine learning algorithms to solve the credit rating problem. These studies are as follows;

Jadhav et al. (2018) addressed the classification and attribute subset selection problem together to solve the individual credit rating problem. Variables are behavioural variables such as age, marital status, home ownership status, number of loans used before, loan maturity, etc., that define the individual customer. After feature selection among SVM, KNN, and NB machine learning algorithms, the accuracy rate of the SVM algorithm is higher in all datasets compared to KNN and NB algorithms. Similarly, by using the feature selection technique to reduce the independent variables in a personal credit rating, Teles et al. (2020) developed an ANN-based decision support system study conducted by a bank in Brazil. They concluded that the uncertainty in the credit rating process makes it possible to model with fuzzy logic. However, the CART model is particularly convenient for solving this problem. Maldonado, Pérez, et al. (2017) used a dataset of 7,309 loans from a Chilean bank, granted between 2004 and 2007, and repaid in monthly instalments to small and micro companies. The data set contains 676 variables that characterise loans, borrowers and the borrowers' financial history available to all returning customers. Given the numerous variables involved, the feature selection technique with the SVM algorithm was applied, yielding successful results. Nalić et al. (2020) investigated the superiority of feature selection techniques over the PCA technique (Principal Component Analysis) using the RF and CART algorithms, and the proposed model was more successful according to the results. Azhagusundari and Thanamani (2013) focused on classifying retail loans, employing a feature selection technique that demonstrated enhanced model performance. Trivedi (2020) utilised twenty independent variables, along with feature selection techniques, to extract the most informative feature set from a dataset containing one dependent variable. The study employed German loan data from the UCI datasets for consumer loans. A comparative analysis was conducted to estimate credit scoring across various machine learning classifiers and feature selection techniques, including NB, RF, CART and SVM.

Thanks to the feature selection method, unimportant variables are eliminated, thereby increasing the model's accuracy. The feature selection technique can be used for four primary purposes: simplifying the model by reducing the number of parameters, reducing training time, reducing excess error by improving generalisation, and mitigating the linear connection problem (Chen et al., 2020). Traditional feature selection approaches for machine learning are broadly categorised into three primary methods: filter methods, wrapper methods, and embedded methods (Jain & Singh, 2018). Some research employs filter methods of feature selection, as seen in studies by Chen and Li (2010) and Hajek and Michalak (2013). Similarly, while some studies employ wrapper methods of feature selection, such as those by Jadhav et al. (2018) and Oreski and Oreski (2014), others utilise embedded feature selection methods, as seen in the work by Chen et al. (2012) and Maldonado et al. (2017).

The filter method ranks features based on evaluation criteria, typically using correlation-based scores. Features below a certain threshold are discarded, while those above are retained. Unlike other methods, it is classifier-agnostic, reducing bias and the risk of overfitting. Its main advantage is computational efficiency, making it ideal for high-dimensional data, as it requires fewer resources than wrapper and embedded methods. Despite potentially overlooking feature interactions, its effectiveness and independence from classifiers make it a valuable tool for large-scale datasets (John et al., 1994; Pudjihartono et al., 2022).

This study chooses the filtering method from the feature selection methods after using six different classification algorithms with the same dataset. Thanks to the preference of this feature selection method, it aims to prevent the data from fitting excessively according to the classification algorithm.

2.3. Credit Rating and Independent Variables

The independent variables used in the studies on commercial loans in the literature are summarised below.

Aygün and Toptan (2018) surveyed bank commercial loan officials to determine what affects the creditworthiness of companies in commercial credit evaluation. They determined that the variables of Financial Payables, Capital, Trade Payables, Sales, Trade Receivables, Profit for the Period, Inventories, Liquid Assets, and Tangible Fixed Assets are essential. In their study, Akdoğan and Tenker (2007) used the variables of Trade Receivables, Inventories, and Trade Payables. On the other hand, Sönmez et al. (2015) investigated the estimation of deposit bank profitability using the ANN algorithm, incorporating current, liquidity, and cash ratios. Yenisu (2019) used the Liquidity ratio, Current ratio, Cash ratio, Trade Receivables, Inventories, Expenses for Future Months, Financial Fixed Assets, Trade Payables, and Capital variables to measure a company's performance. In Şahin's (2021) study, the performance of the Turkish trade sector is evaluated between 2009 and 2019 using the following variables: Trade Receivables, Inventories, Tangible Fixed Assets, Bank Loans, Trade Payables, Vendors, Capital, Net Profit for the Period, Retained Earnings, and Financial Expense. Kızıl et al. (2020) for commercial credit evaluation; Buyers, Inventories, Advances given, Expenses for future months, Tangible Fixed Assets, Trade Payables, Advances Received, Trade Payables, Paid Capital, Retained Earnings, Net Profit for the Period, Net Sales, Financial Expense variables are used.

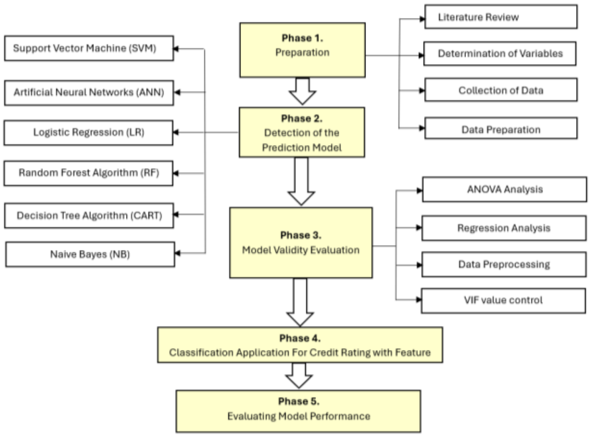
2.4. Research Gaps

The literature review seen above highlights significant gaps in credit rating studies. Previous studies typically classify credit loan applicants as either “rejection” or “acceptance,” or as “good customer” or “bad customer,” using machine learning algorithms. Unlike the existing literature, this study makes a significant contribution by presenting a novel model that can classify a customer's current limit as either “increasing” or “decreasing”. Additionally, the literature indicates that studies on commercial loans are notably fewer in number than those on individual credit ratings and often rely on historical customer data. However, a key objective for banks is to acquire new customers. Unlike previous studies focusing on historical customer data and intuitive characteristics, this research utilises financial variables from independent audit reports shared as open data, omitting past customer behaviour and including potential new customers. This innovative approach contributes to the literature by establishing a commercial credit decision support system that operates without prior customer history. Moreover, literature research indicates that the scarcity of studies that utilise feature selection methods in conjunction with machine learning algorithms for credit rating is notable. For this reason, this study addresses this void by applying feature selection techniques to six algorithms using real commercial customer data, thereby enhancing model accuracy and demonstrating the effectiveness of feature selection in credit rating applications.

3. Methodology

This research introduces a novel framework aimed at categorising the current lending limit of customers into “increasing” or “decreasing” categories, a pivotal task within banking operations. Identifying variables with strong predictive capabilities is crucial for ensuring the model's efficacy. Hence, a combination of feature selection techniques and machine learning algorithms was employed to assess the impact of variables identified through literature review and expert insights on the dependent variable.

Figure: 2
Proposed Predictive Framework



The following research methodology is shown in Fig. 2. The Research methodology consists of five main phases. As shown, the first phase involves a literature review to identify machine learning algorithms. The second phase combines a literature review on variables with real experiences. In the third phase, to investigate whether there is a multicollinearity problem, VIF values are calculated, and then ANOVA and regression analyses are performed. In the fourth phase, machine learning algorithms were combined with a feature selection method for the classification application in credit rating purposes. The final phase involves evaluating the model's performance.

The remainder of this section presents the research's data and variables, as well as the machine learning algorithms employed.

3.1. Data and Variables

The data are obtained from the address <https://www.kap.org.tr/tr/> where the approved independent audit reports containing the financial data of the companies offered to the public in Türkiye are shared. Financial data approved by each company's independent audit is published four times a year. According to the Merkezi Kayıt Kuruluşu A.Ş. (MKK)

Statistics reports, the number of companies that went public and were traded at the end of 2022 was 525. Since 8 of the 525 companies went public in the last quarter of 2022, they were excluded from the sample population. The total population consists of 517 companies. This study utilised financial data from 80 companies out of 517 listed on the link <https://www.kap.org.tr/tr/bist-sirketler>. The financial data for 2012-2022, comprising four periods per year, were used. The selection of 80 companies out of 517 companies was made because the data for the past ten years was available. Since the data obtained from other companies cover short periods such as three or five years, they were not included in the sample in this study. The availability of independent audit reports for the past ten years and the selection of companies whose shares were publicly traded as a sample constituted the limits of the data set used in the study. Eighty companies out of 517 are sufficient in terms of sample acceptance and representativeness. The fact that the data span a 10-year period increases the reliability of the study.

The dataset has been divided into 80% training and 20% test data splits. The classification of credit limits as "increasing" or "decreasing" within the dataset is based on the change in total credit size relative to the previous financial period of the company. For example, if the credit size in December 2022 has increased compared to June 2022, it is categorised as "increasing"; if it has decreased, it is classified as "decreasing". Based on these classifications, this proposed method aims to develop a predictive model to facilitate decisions on increasing or decreasing the credit limit in the subsequent financial period.

Table: 2
Financial Variable List and Definition

Financial Variable Name	Financial Variable Definition
Cash and Cash Equivalents	Money in physical safes or bank accounts is intended for spending.
Commercial Debts	Receivables, whether with or without promissory notes, must be collected within one year.
Stocks	It consists of assets that are likely to be sold within one year.
Prepaid Expenses	These are the accounts in which the amounts paid before the maturity of the enterprise's expenses are followed.
Tangible Assets	They are physical assets, such as a factory building, that have been purchased for use.
Trade Payables	All debts due within one year arising from the business's purchases.
Paid-in Capital	It includes the money that partners transfer to the business.
Period Profit/Loss	It shows the final profit or loss at the end of the operating period.
Previous Year Profit/Loss	It is the sum of the profits/losses of the previous accounting periods.
Revenues	It is the money obtained from the sale of goods and services resulting from the business's activities.
Financing Expenses	It includes interest, commission, and similar business expenses.
Short-Term Debt	It covers foreign resources (such as bank debt) that the business can pay within a year.
Short-Term D.From Long-Term D.	It consists of the principal instalments of long-term loans to be paid within the year.
Long-Term Bank D.	It covers foreign resources (bank debt) that the business will pay in over a year.
Increasing Credit or Decreasing? (The Dependent Variable)	A Total Credit Limit Size is a dependent variable that expresses the change in the sum of the Long-Term Bank Debt and Short-Term Debt variables, from Long-Term Debt to Short-Term Debt, compared to the previous period.
Current Assets	It consists of cash and assets held in the bank, as well as items expected to be consumed during the year.
Short-Term Foreign Resources	Foreign sources include principal instalments and interest on debts.
Current rate	The working capital or current ratio is calculated by dividing total current assets by total short-term liabilities. This ratio provides insight into a company's ability to meet its short-term obligations using its current assets.
Liquidity Ratio	It represents the capacity of a business to fulfil its short-term obligations as they become due.
Cash Ratio	It represents the ability of businesses to pay their current debts if their activities are halted and they are unable to collect their receivables from the market.

The selection of independent variables comprises the financial data presented in the independent audit reports published by the companies. Under the legislation, independent audit reports must be examined and approved by certified public accountants, which increases the reliability of financial data, so independent audit reports are considered in this study. The variables selected through literature research and expert opinions, along with their definitions, are shown in Table 2 above. Nineteen independent and one dependent variable were used in the study.

In this research, a feature selection technique was employed to identify the independent variables that can be used to predict the direction of the credit limit, thereby solving the classification problem. A feature selection technique is the name given to create a correct representation capability by evaluating the variables individually to determine which variables affect the result and how they affect it.

3.2. Machine Learning Algorithms Used in Research and Feature Selection

This study employs six widely used machine learning algorithms to classify the direction of commercial loans. Additionally, it is observed that the literature utilises five different metrics to evaluate the performance of various prediction algorithms. These metrics include:

Accuracy: Reflects the proportion of correct predictions made by the model out of all predictions.

Precision: Indicates the percentage of samples predicted as positive that were correctly predicted.

Sensitivity: Measures the model's capability to accurately identify positive examples.

Selectivity: Evaluates the model's ability to identify negative examples accurately.

F-score: Represents the harmonic mean of precision and sensitivity, providing a balanced measure of model performance.

These metrics provide a comprehensive evaluation of the predictive capabilities of the machine learning algorithms used in the study. These performance metrics are as follows (Rifatv et al., 2019);

- Accuracy rate = $\frac{TP+TN}{TP+FP+TN+FN}$
- Precision = $\frac{TP}{TP+FP}$
- Sensitivity = Recall = $\frac{TP}{TP+FN}$
- Selectivity = Specificity = $\frac{TN}{TN+FP}$
- F-score = 2 x $\frac{(recall\ x\ precision)}{(recall+precision)}$

The metrics described above evaluate the model's prediction performance across four categories: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

True Positive (TP): Indicates the number of positive class examples the model correctly predicted.

True Negative (TN): Represents the number of negative class instances the model correctly predicted.

False Positive (FP): Reflects the number of positive class examples the model incorrectly predicted.

False Negative (FN): Represents the number of negative class instances the model incorrectly predicted.

These metrics provide a detailed assessment of the model's performance by considering correct and incorrect predictions across different classes. The machine learning algorithms used in this study are summarised below.

3.2.1. Support Vector Machine Algorithm

Following the pioneering studies of Lerner and Vapnik in 1963 and subsequent work by Chervonenkis and Vapnik in 1964, the concepts established were further developed and applied by Vapnik and Cortes in 1995. Their work extended the application of these concepts into various fields, including text analysis, speech recognition, and time series prediction (Cortes & Vapnik, 1995). SVM is a machine learning technique that can do supervised and unsupervised learning. This algorithm is frequently used in the literature to solve various problems, including credit rating. SVM attempts to find the optimal hyperplane that separates different classes with a high correct prediction rate.

3.2.2. Artificial Neural Networks Algorithm

ANNs are an artificial intelligence technique that enables the modelling and solution of complex problems, drawing inspiration from the functioning of nerve cells in the human brain. The development of ANNs can be traced back to the logical calculations of neural activity proposed in 1943 (Warren & Walter, 1943). ANN consists of input, hidden layers and output parts in its simple form. As a result of the development of communication between nerves and neurons in the brain, it has been observed in the literature that ANN algorithms are frequently employed, particularly in estimation problems.

3.2.3. Logistic Regression

The Logistic Regression (LR) algorithm is favoured for its simplicity and straightforward implementation. However, many real-world classification problems exhibit nonlinear relationships. In its fundamental form, Logistic Regression (LR) is a statistical model that utilises a logistic function to characterise a binary dependent variable, thus earning it the moniker "binary LR algorithm". The logistic model estimates the probability of a specific class or event occurrence. To address scenarios involving multiple classes of events, LR can be extended into a polynomial LR algorithm model, allowing for the modelling of several classes of events. This extension enables LR to handle more complex classification tasks beyond binary outcomes (Ning et al., 2023).

3.2.4. Random Forest Algorithm

The Random Forest algorithm derives its name from its key components: "random" and "forest". The "random" aspect involves two key elements: Random data selection. The algorithm randomly samples data from the dataset to create subsets, known as bootstrap samples. The ultimate prediction of the Random Forest model is derived by consolidating the predictions made by each tree. This typically involves employing a majority voting scheme for classification tasks or averaging for regression tasks. By leveraging randomness in data sampling and feature selection, Random Forests create an ensemble of diverse decision trees, yielding robust and accurate predictions for classification and regression problems (Liu et al., 2023).

3.2.5. Decision Trees Algorithm

In the CART algorithm, the flow elements connecting the root node to the leaf nodes are referred to as branches. The data entry occurs at the root node, from which the decision-making process begins. Internal nodes, or branches, represent decision points where the dataset is partitioned based on the values of selected features. These branches guide the data flow down the tree structure, ultimately leading to the assignment of samples to leaf nodes, which represent the final decision outcomes. Therefore, internal nodes and leaf nodes are fundamental components used to construct the decision structure in CART. The process of asking questions about the problem and advancing to a conclusion in line with the results obtained using the data transferred to the tree for decision-making, starting with the root node, is a decision tree working style (Pal & Mather, 2003).

3.2.6. Naive Bayes Networks

NB are mathematical models. Variables contain several different possibilities, including possible cases. Edges represent direct dependencies of two variables, and by connecting them, they create conditional causality. This approach represents stochastic prior relationships used to calculate the probability that one case will influence the occurrence of another case (Cypko et al., 2017).

3.2.7. Feature Selection

Feature selection is pivotal in machine learning applications, particularly within financial domains such as credit limit assessment. The primary objectives of feature selection are to enhance model performance, mitigate the risk of overfitting, and ensure interpretability. Accurately identifying the variables that influence credit limits fortifies the risk management strategies of financial institutions and enhances the quality of services offered to customers. The significance of feature selection in this context can be delineated as follows: First, it contributes to improved model performance. In machine learning models designed to predict credit limits, including superfluous or irrelevant features can have a detrimental impact on the overall model efficacy. Feature selection enhances the model's predictive power by isolating the most pertinent variables. Second, it plays a crucial role in preventing overfitting. Overfitting occurs when a model excessively conforms to the training data, resulting in subpar performance on unseen datasets. By identifying and retaining only the most relevant features, feature selection diminishes this risk and bolsters the model's generalisation capability. Third, feature selection fosters interpretability. The model becomes more comprehensible by reducing the variables involved in credit limit determination. This increased clarity enhances transparency in the decision-making processes of lending institutions, allowing users to understand their financial circumstances better. In conclusion, feature selection is integral to the credit limit decision-making framework. The judicious selection of variables enhances model performance and promotes transparency and reliability in credit assessment processes.

4. The Proposed Model

In this study, a model is presented that aims to determine the direction of the credit limit for customers in lending activities, one of the primary duties of banks, and which can produce predictions using machine learning methods by focusing on relevant variables. During the research, the IBM SPSS Modeller and KNIME programs were used for the analyses performed.

4.1. Data Preprocessing and Model Validity Testing

In the regression analysis to assess the relationship between the credit limit and selected variables identified through literature review and expert opinions, variance inflation factors (VIFs) were computed using the KNIME program. VIF values indicate the extent of multicollinearity among independent variables. Specifically, VIF is calculated by examining the diagonal elements of the inverse of the correlation matrix for the independent variables. If the VIF for a variable is greater than or equal to 10, it indicates a multicollinearity problem, signifying high correlation between that variable and others (Koçoğlu & Ersöz, 2022). When the VIF values are examined in the analysis, as seen in Table 3, Current Assets and Short-Term Liabilities are excluded from the model because they create a multicollinearity problem. The stock variable was not excluded from the model due to expert opinion, its frequent occurrence in the literature, and the fact that it exceeded the limit by 10% in terms of VIF Value.

Table: 3
VIF Values for the Data Set

Variable	VIF Value
Current assets	46.00
Short-Term Foreign Resources	38.40
Stocks	11.24
Other Variables	Value ≤ 10

The model disclosure rate of the variables was investigated using the SPSS program. While performing this analysis, we excluded Current Assets and Short-Term Liabilities with high VIF values from the model. They were excluded from the study because they created a multicollinearity problem. According to the summary model outputs in Table 4 below, the adjusted model disclosure ratio (R^2) of the data was 0.836. It can be said that the R^2 value found is very high in terms of explaining the model of the variables used in the research.

Table: 4
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,915[a]	,837	,836	141682332

Analysis of variance (ANOVA) is a parametric inferential statistical method used to test whether there is a statistically significant difference between population averages. The model is valid as $p=0.00<0.05$ for the Analysis of Variance results in Table 5 below (Ersöz & Ersöz, 2020). The model's validity suggests that the independent variables have a significant impact on the direction of the dependent variable, the credit limit. The model's validity enhances the reliability of the prediction rate in machine learning work that generates predictions.

Table: 5
Variance Analysis Results

ANOVA						
Model		Sum of Squares	df	Mean Square	F	p.
1	Regression	2,9054E+22	14	2,07529E+21	1033,825	0,000
	Residual	5,64879E+21	2814	2,00739E+18		
	Total	3,47028E+22	2828			

To ensure the validity of the model, after evaluating multiple linear connections, model explanation ratios and variance analysis were performed as explained above. Regression analysis was then conducted to identify the variables that affect the credit limit in the study. As shown in Table 6, regression analysis was performed using 14 independent variables, which were selected from a total of 19 independent variables. Note that the Current Assets and Short-Term Liabilities variables were excluded from the analysis due to the high VIF values. In addition to this, the sum of three variables, which are Short-Term Borrowings, Short-Term Debt from Long-Term Debt, and Long-Term Bank Debt, constitutes the dependent variable, which classifies the direction of total loan size. For this reason, these three variables were also excluded. According to the regression analysis results presented in Table 6 below, except for the Cash Ratio variable, all variables significantly affected the estimation of credit limits ($p < 0.05$). In the subsequent analyses, the Cash Ratio variable was excluded from the model.

Table: 6
Regression Analysis Result

Model	Unstandardised Coefficients		Standardised Coefficients	t-value	*P*
	B	Std. Error	Beta		
Constant	506623421.4	61870326.89		8,188	<,001
Cash and Cash equivalents	0,596	0,028	0,293	21,354	<,001
Commercial Debts	0,099	0,047	0,039	2,11	0,035
Stocks	-0,306	0,033	-0,203	-9,186	<,001
Prepaid expenses	0,446	0,068	0,06	6,601	<,001
Tangible Fixed Assets	0,269	0,012	0,346	21,831	<,001
Trade Payables	0,178	0,038	0,089	4,639	<,001
Paid-in Capital	0,151	0,064	0,028	2,369	0,018
Profit For the Period (Loss)	-0,758	0,066	-0,205	-11,497	<,001
Previous year's Profit and Loss	0,154	0,033	0,084	4,616	<,001
Revenues	0,04	0,009	0,081	4,23	<,001
Financial Expenses	2,158	0,05	0,476	43,403	0,00
Current Rate	-521015241	89712013,1	-0,121	-5,808	<,001
Liquidity Ratio	422596560	121917570	0,077	3,466	<,001
Cash Ratio	-113684601	89026666,3	-0,014	-1,277	0,202

4.2. Classification Performance Comparison

In this study, classification algorithms were applied in conjunction with feature selection techniques. By determining how the selected variables affect the model's performance, it is aimed to choose the algorithm that yields the highest prediction success rate with the optimal number of variables. In practice, the Current Assets and Short-Term Liabilities variables were excluded from the analysis because their VIF values were high. Additionally, the regression analysis revealed that the Cash Ratio variable had no significant impact on the credit limit, and therefore, it was not included in the feature selection application.

The algorithms employed in this study, SVM, ANN, LR, RF, CART, and NB, are well-established in the machine learning literature on credit scoring. These algorithms are selected based on several key factors: Dataset Complexity; Our dataset features nonlinear relationships and numerous attributes, making SVM and ANN particularly suitable due to their ability to handle high-dimensional data effectively. Proven Effectiveness: These algorithms have been successfully applied in credit limit estimation and similar classification tasks. For instance, RF and CART demonstrate strong classification performance, achieving high accuracy even with imbalanced datasets, which supports their use in our analysis. Flexibility and Adaptability; The literature indicates that these algorithms can easily adapt to various data types and problems. Notably, RF's ensemble approach offers significant advantages in achieving reliable results in critical applications, such as credit scoring. In conclusion, our choice of algorithms reflects the characteristics of the dataset and their established effectiveness in the literature, thereby reinforcing the methodological rigour of our study.

Analyses were made using the KNIME data mining program to evaluate the increase or decrease of the bank credit limit. The number of iterations and layers was tested in the ANN algorithm, and it was found that the optimum accuracy rate was achieved at 185 iterations and 10 layers. To evaluate the performance of the algorithms used in this research, which are frequently seen in the literature, we consider accuracy, F-score, selectivity, sensitivity, and precision.

As shown in Table 7 below, the RF algorithm achieved the highest success rate when its prediction accuracy performance was compared after applying the feature selection technique. The order of success of the other algorithms in terms of accuracy rate is as follows: ANN, LR, SVM, NB, and CART. The feature selection technique has increased the accuracy rate in all algorithms, but the increase rates vary. The order of the feature selection techniques, from highest to lowest, has been determined as follows: NB, ANN, RF, SVM, and CART algorithms. While the accuracy rate of the NB algorithm before feature selection was 42.60%, it increased to 63.40% after feature selection was applied. While the accuracy rate of the ANN algorithm was 61.30% before feature selection, it increased to 67.30% after feature selection was applied. While the accuracy rate of the RF algorithm before feature selection was 64.10%, it increased to 69.40% after feature selection was applied. While the accuracy rate of the SVM algorithm before feature selection was 59.50%, the accuracy rate after feature selection was 63.40%. While the accuracy rate of the CART algorithm before feature selection was 59.40%, the accuracy rate after feature selection was 63.10%. In this study, after feature selection, the algorithm that increases the accuracy rate the most is the NB algorithm, and, remarkably, the effect of the feature selection technique on this algorithm is high.

Table: 7
Classification Performance Comparison

Algorithm	Accuracy Before Feature Selection	Rate	Precision	Sensitivity	Selectivity	F-Score	Accuracy Rate After Feature Selection	Number of Variables Selected
RF	64,10%	Increasing	0.67	0.82	0.35	0.75	69,40%	9
		Decreasing	0.54	0.35	0.82	0.42		
ANN	61,30%	Increasing	0.66	0.77	0.36	0.71	67,30%	8
		Decreasing	0.49	0.36	0.77	0.41		
LR	61,30%	Increasing	0.62	0.95	0.06	0.74	63,60%	5
		Decreasing	0.45	0.06	0.95	0.11		
SVM	59,50%	Increasing	0.62	0.89	0.11	0.73	63,40%	9
		Decreasing	0.39	0.11	0.89	0.17		
NB	42,60%	Increasing	0.60	0.13	0.91	0.22	63,40%	2
		Decreasing	0.39	0.91	0.13	0.55		
CART	59,40%	Increasing	0.67	0.68	0.45	0.67	63,10%	8
		Decreasing	0.47	0.45	0.68	0.46		

Regarding precision values, both the RF and CART algorithms demonstrate similar success in credit limit increase decisions. The RF algorithm is more successful than others in decreasing credit limit decisions. Regarding sensitivity values, the success rates for credit limit increase decisions are as follows: LR, SVM, RF, ANN, CART, and NB. Regarding selectivity values, the success rates in credit limit decrease decisions are as follows: LR, SVM, RF, CART, and NB.

Regarding F-score values, the RF algorithm is more successful than others in credit limit increase decisions. A high F-score value indicates that we likely have high sensitivity, and a significant portion of the decision will be recalled, indicating the model will exhibit high learning ability. Low F-score values mean it did not perform well in most test sets. Therefore, the success of the RF algorithm is also determined by the F-score value.

A low Precision value means it cannot correctly detect most cases defined as positive cases. A precision score of 1 indicates the model does not miss any true positives and can classify well between correctly and incorrectly labelling credit lines. This demonstrates the high success of the RF algorithm, which shows a precision value of 0.67.

The sensitivity value measures the model's ability to correctly identify positive samples. A Sensitivity value approaching 1 indicates that the model can make a reasonable classification between correct and incorrect labelling of the credit limit. For this reason, the RF algorithm shows high success with a Sensitivity value of 0.82.

5. Conclusion

This study introduces a machine learning model designed to classify whether a customer's current lending limit will increase or decrease, addressing one of the primary responsibilities of banks. A regression analysis was conducted to examine the relationship between the credit limit and variables identified through literature research and expert opinions. Feature selection techniques were utilised to identify and incorporate important variables into the model. To enhance the model's practical applicability and aid decision-making, various machine learning algorithms, including SVM, ANN, LR, RF, CART, and NB, were compared based on their predictive performance. This comparative analysis aimed to identify the most effective algorithm for the task.

This model shifts the focus from binary classifications to a dynamic assessment of customer relationships, allowing banks to tailor credit strategies based on individual risk profiles. Providing detailed insights on how this approach leads to more informed credit decisions, enhances customer satisfaction, and reduces potential losses would offer clearer perspectives. By dynamically predicting changes in credit limits, the model has three significant practical impacts. Firstly, banks can set more accurate credit limits based on changes in a customer's financial situation, thereby strengthening risk management. Secondly, dynamic limits better respond to customer needs, increasing satisfaction and loyalty. Lastly, regularly reviewing credit limits enables banks to detect risky situations early, mitigating potential losses. This approach enhances risk management strategies, boosting financial stability and strengthening customer relationships.

In the literature, it has been observed that some researchers neglected to classify the bank for credit rating and instead focused solely on comparing the performance of machine learning algorithms against one another. For example, when performing credit ratings, Hu and Su (2022) reduced 133 variables to 13 by performing factor analysis and comparing them through model performance criteria. Their model does not provide a classification result, such as identifying good or bad customers, or acceptance or rejection for the bank. Instead, it only compares the advantages of the algorithms with each other. Similarly, Derelioğlu et al. (2009) identified 512 variables while performing credit rating and used the feature selection technique to reduce the variables. As a result of the research, the performances of machine learning algorithms were compared. Some researchers have preferred to use variables that provide instantaneous evaluations of the past behaviour of banks' commercial customers, such as the loan amount the commercial customer is currently applying for or the loan interest rate. For example, Zekic-Susac et al. (2004) used variables such as loan interest rate, loan request amount, and grace period duration in their study. As a result of these variables, the customer is classified as "good" or "bad". However, banks do not evaluate the limits of commercial customers once. After opening a limit that can be used within a year, they keep this limit open continuously, allowing the customer to use it whenever they request it. Therefore, the interest rate may change weekly or monthly throughout the year, and the number of maturities the bank can give is also significant, apart from the loan term requested by the customer. Banks may offer loans at the maturity recommended by the bank, rather than at the maturity desired by the commercial customer. Similarly, Giannouli and Kountzakis (2019) compared companies based on their performance and classified them as either good or bad. At the same time, prior studies have often focused on classifying commercial customers as "good" or "bad"; this study offers a novel perspective by emphasising a more nuanced evaluation of credit limits. Banks do not simply decide to approve or deny loans based on these classifications. Instead, they consider the potential credit that can be extended to each customer, even if that customer may appear to be a risk. For instance, a customer deemed "bad" might still be eligible for a smaller credit limit, and overlooking this could result in lost revenue for the bank. Therefore, our model advocates for strategies that suggest increasing a customer's current limit or managing their debt burden effectively, ultimately enhancing the bank's income. Conversely, reducing credit limits or debt burden may mitigate potential income losses. By acknowledging the complexities of customer relationships and integrating insights from prior research, this approach provides a balanced perspective that enhances the overall understanding of effective credit management.

This study makes a significant contribution to the literature by introducing a machine learning model that classifies a customer's credit limit as either "increasing" or "decreasing", thereby addressing a notable gap in existing research. Unlike previous studies, which often focus on individual credit ratings and rely heavily on historical customer profiles, our approach emphasises financial variables pertinent to commercial customers without considering their past behaviour. This shift is crucial for banks aiming to attract new customers and refine their credit evaluation processes.

Credit limits are significantly influenced by various financial variables that reflect an organisation's overall fiscal health. For instance, Cash and Cash Equivalents are a primary liquidity indicator that banks prioritise in their risk assessments. A higher cash position typically indicates a greater ability to meet financial obligations, which in turn positively affects the credit limit. Conversely, Commercial Debts and Short-Term Debt can represent potential risks; elevated levels of these liabilities may raise concerns for lenders about an organisation's ability to manage its debt load, potentially leading to more conservative credit decisions. Additionally, variables such as tangible assets offer collateral value, further enhancing creditworthiness in the eyes of banks. Performance metrics, such as Period Profit/Loss and Previous Year Profit/Loss, indicate profitability trends. Sustained profits bolster confidence in repayment capabilities, which is likely to result in higher credit limits. Moreover, the Liquidity Ratio and Cash Ratio provide insight into an entity's short-term financial health, with higher ratios correlating with lower perceived risk. As such, these financial indicators influence credit limits and inform banks' risk management strategies. In machine learning, incorporating these variables into predictive models can enhance the accuracy of credit risk assessments, enabling more informed lending decisions and potentially benefiting both financial institutions and borrowers alike.

The regression analysis results indicate strong model performance, with an R^2 value of 0.837, suggesting a high level of representational capability. The analysis identified several significant variables that impact credit limit estimations, including “Cash and Cash Equivalents,” “Trade Receivables,” and “Liquidity Ratio,” while the “Cash Ratio” was deemed insignificant. In assessing classification performance, the Random Forest (RF) algorithm achieved the highest accuracy, at 69.40%, outperforming other methods, including ANN, LR, SVM, NB, and CART. The feature selection process enhanced the accuracy of all algorithms, with varying degrees of effectiveness. Notably, the most impactful variables identified after feature selection were aligned with real-world banking concerns, providing practical relevance for banking professionals.

Although deep learning models are widely recognised for their superior performance across a range of complex tasks, several compelling reasons justify the exclusive focus of this study on traditional machine learning models without engaging in comparisons with deep learning approaches. These reasons are outlined as follows: First, Contextual Relevance: The primary objective of this research was to examine specific facets of the credit limit decision-making process through the lens of conventional machine learning techniques. Second, Computational Efficiency: Traditional machine learning models typically require significantly less computational power and training time when compared to their deep learning counterparts. In the context of this study, the application of conventional machine learning methods facilitated a more rapid analysis and expeditious results, which is particularly pertinent given potential resource constraints. Third, Data Size and Complexity: Deep learning models generally demonstrate optimal performance with larger datasets characterised by intricate patterns. In this study, the dataset comprising 80 companies was not sufficiently extensive or complex to justify the implementation of deep learning techniques, especially considering the heightened risk of overfitting associated with such models.

In summary, while the absence of comparisons with deep learning models may be perceived as a limitation, the emphasis on traditional machine learning models represents a strategic choice tailored to meet specific research objectives and practical considerations inherent in the financial context. Future research endeavours may expand upon these insights by incorporating deep learning methodologies.

These findings have significant implications for advancing FinTech technologies, particularly in making accurate credit limit decisions. The financial stakes are high because a bank may need to lend to at least 100 customers to offset a single loan default. The study illustrates how machine learning can enhance predictive capabilities in credit assessment, emphasising the need for banks to adapt their strategies based on empirical evidence.

Moving forward, there is a critical need for further exploration of machine learning techniques within the banking and FinTech sectors. Future research should aim to validate and refine these methodologies, drawing comparisons with existing literature to deepen the theoretical understanding of credit risk assessment. By integrating insights from this study with broader financial applications, we can foster a more robust framework for effective banking practices and decision-making.

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